MrPaw

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Are US non-voters becoming more Republican?

Blue Rose research says yes:

“Politically disengaged voters have become much more Republican, And because less-engaged voters swung away from [Democrats], an expanded electorate meant a more Republican electorate.”

[Blue Rose Research, 2024] (On Ezra Klein show, major professional pollsters)

***On Data and Democracy* says no:**

“Claims of a decisive pro-Republican shift among the overall non-voting population are not supported by the most reliable, large-scale post-election data currently available.”

[Bonica et al., 2025] (Berkeley professor co–author, major professional researchers)

- The problem is very hard (it’s difficult to accurately poll non–voters)
- Different data sources
- **Very different statistical methods:** ⋆
  - Blue Rose uses Bayesian hierarchical modeling (MrP)
  - The CES uses weighted averages (calibration weighting)

Our contribution

We provide a calibration weighting interpretation of MrP analyses that:

- Is easily computable from MCMC draws and standard software, and
- Defines MrP versions of key diagnostics that motivate calibration weighting.

We provide apples-to-apples comparisons between MrP and calibration weighting.

Outline

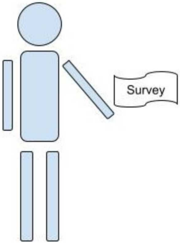
- Introduce the statisical problem and two methods (calibration weighting and MrP)
- Describe one of the classical calibration weighting diagnostics (covariate balance)
- Define MrPaw & state a key theorem
- Real-world results
- Future directions

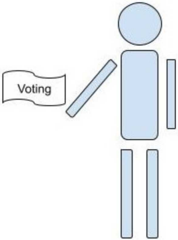
The basic problem

We have a survey population, for whom we observe:

- Covariates $\mathbf{x}$ (e.g. race, gender, zip code, age, education level)
- Responses y (e.g. A binary response to "do you support policy such–and–such")

We want the average response in a target population, in which we observe only covariates.





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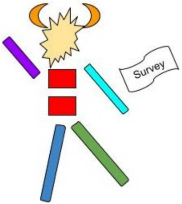

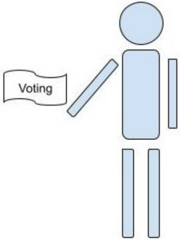

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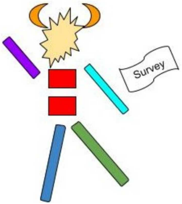

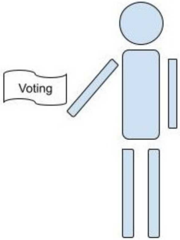

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Our survey results may be biased.

How can we use the covariates to say something about the target responses?

Two approaches

We want $\mu := \frac{1}{T} \sum_{t=1}^{T} y_t$, but don't observe target population y_t.

- Assume $p(y|\mathbf{x})$ is the same in both populations,
- But the distribution of $\mathbf{x}$ may be different in the survey and target.

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► Choose "calibration weights" w_s
(e.g. raking weights)

Bayesian hierarchical modeling (MrP)

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▶ **Black box**

$\leftarrow$ (We open this box, providing analogues of all these diagnostics)

What are we weighting for?[1]

We want:

$$\text{Target average response} = \frac{1}{T}\sum_{t=1}^{T} y_p \approx \frac{1}{S}\sum_{s=1}^{S} w_s y_s = \text{Weighted survey average response}$$

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You can check covariate balance for any calibration weighting estimator.

Even more, covariate balance is the criterion for a popular class of calibration weight estimators:

Raking calibration weights

"Raking" selects weights that

- Are as "close as possible" to some reference weights
- Under the constraint that they balance some selected regressors.

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Generalized covariate balance checks

We want to balance $f(\mathbf{x})$ because we think $\mathbb{E}[y|\mathbf{x}]$ might plausibly vary $\propto f(\mathbf{x})$, and want to check whether our estimator can capture this variability.

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Generalized covariate balance (GCB) (informal)

Pick a small δ, and define a *new response variable* $\tilde{y}$ such that

$$\mathbb{E}\left[\tilde{y}|\mathbf{x}\right] = \mathbb{E}\left[y|\mathbf{x}\right] + \delta f(\mathbf{x}).$$

We know the change this is supposed to induce in the target population.

Covariate balance checks whether our estimators produce the same change.

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We know the expected change this perturbation produces in the target distribution:

$$\mathbb{E}\left[\mu(\tilde{y}) - \mu(y)|\mathbf{x}\right] = \frac{1}{T}\sum_{t=1}^{T}\left(\mathbb{E}\left[\tilde{y}|\mathbf{x}_p\right] - \mathbb{E}\left[y|\mathbf{x}_p\right]\right) = \delta\frac{1}{T}\sum_{t=1}^{T} f(\mathbf{x}_p)$$

Then, check whether your estimator $\hat{\mu}(\cdot)$ produces the same change:

$$\underbrace{\hat{\mu}(\tilde{y}) - \hat{\mu}(y)}_{\substack{\text{Replace weighted averages}\\\text{with changes in an estimator}}} \overset{\text{check}}{=} \delta\frac{1}{T}\sum_{t=1}^{T} f(\mathbf{x}_p).$$

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When $\hat{\mu}(\cdot) = \hat{\mu}_{\text{CAL}}(\cdot)$, GCB recovers the standard covariate balance check.

Generalized covariate balance for MrP

Step one: Construct $\tilde{y}$ such that $\mathbb{E}\left[\tilde{y}|\mathbf{x}\right] = \mathbb{E}\left[y|\mathbf{x}\right] + \delta f(\mathbf{x})$.

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Two possibilities:

- Allow $\tilde{y}$ to take values other than $\{0, 1\}$ and set $\tilde{y} = y + \delta f(\mathbf{x})$, or
- Use an estimate of $\mathbb{E}\left[y|\mathbf{x}\right]$ to draw new binary $\tilde{y}$.

We define theory and methods for the first, and provide tools for generating data using the second method for potentially problematic regressors.

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Taylor series

Form the approximation

$$\hat{\mu}_{\mathrm{MRP}}(\tilde{y}) = \sum_{s=1}^{S} w_s^{\mathrm{MRP}} (\tilde{y}_s - y_s) + \text{Residual} \quad \text{where} \quad w_s^{\mathrm{MRP}} := \frac{d}{dy_s} \hat{\mu}_{\mathrm{MRP}}(y).$$

If MrP were linear (e.g. if you use OLS instead of hierarchical logistic regression), then

- The residual is zero,
- $\hat{\mu}_{\mathrm{MRP}}(y) = \sum_{s=1}^{S} w_s^{\mathrm{MRP}} y_s$, and so
- $\hat{\mu}_{\mathrm{MRP}}(\tilde{y})$ is a calibration weighting estimator, and w_s^{MRP} are its weights. (Cite Gelman)

In general, MrP is truly nonlinear. The residual is only small when $\tilde{y} \approx y$ (i.e., when $\delta \ll 1$).

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It happens that the needed derivatives are given by simple a posterior covariances involving only the inverse link function $m(\mathbf{x}; \theta)$ and log likelihood [Giordano et al., 2018].

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